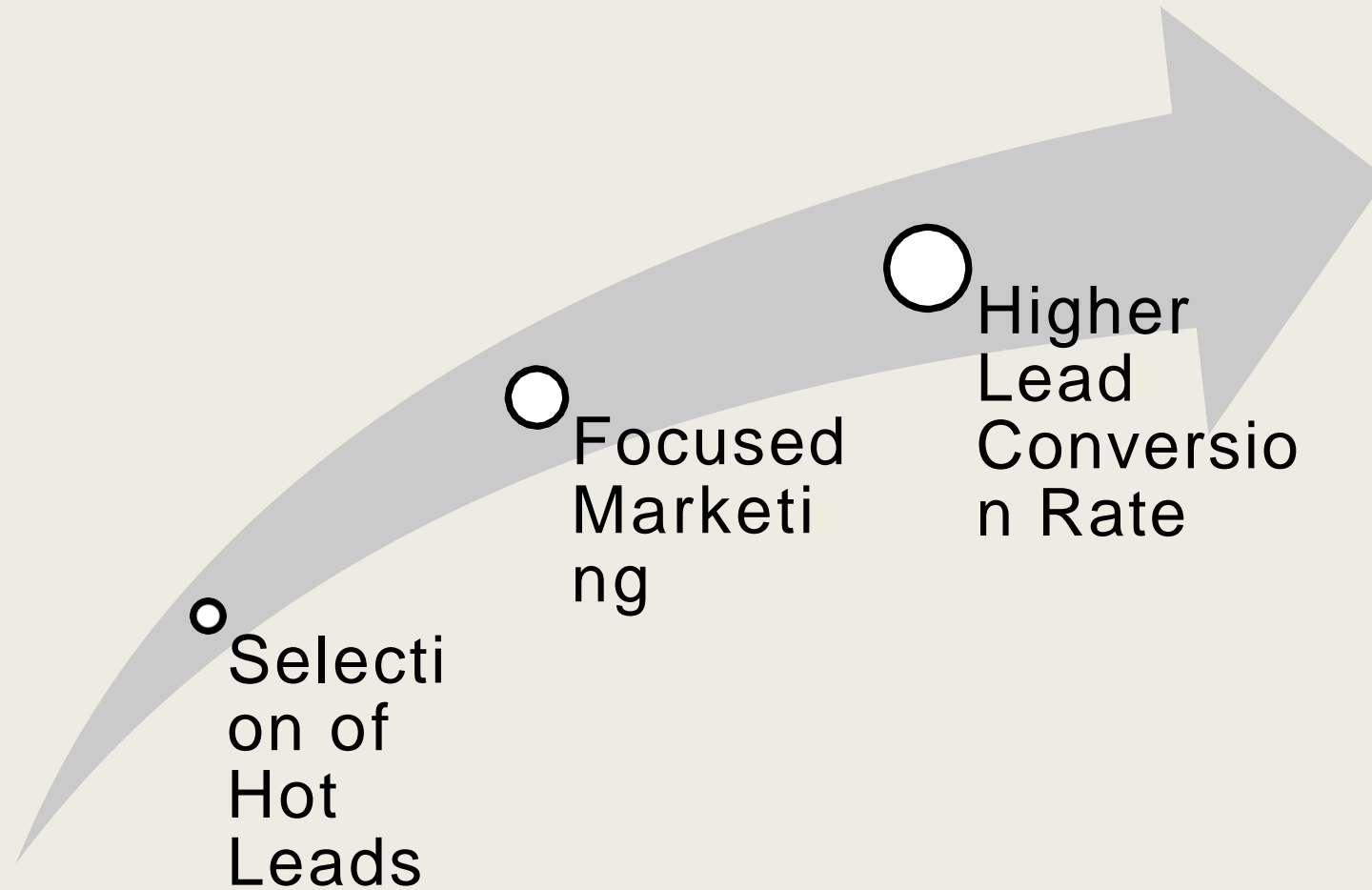# Business Objective

LEAD SCOREING CASE STUDY

BY . RADHA J

To help X Education select most promising leads *(Hot Leads)*, i.e. the leads that are
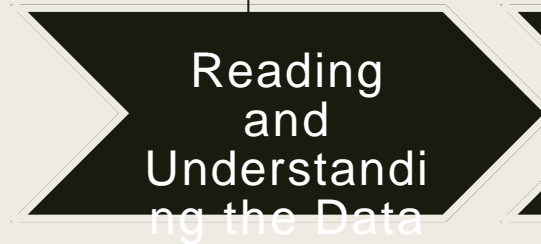
most likely to convert into paying customers.

Selection of Hot Leads

Focused Marketing

Higher Lead Conversion Rate

Importing and Observing the past data provided by

Univariate and Bivariate

the
Company

analysis

Reading and Understanding the Data

Data Cleaning

Exploratory Data Analysis

Data Preparation

- Missing value imputation
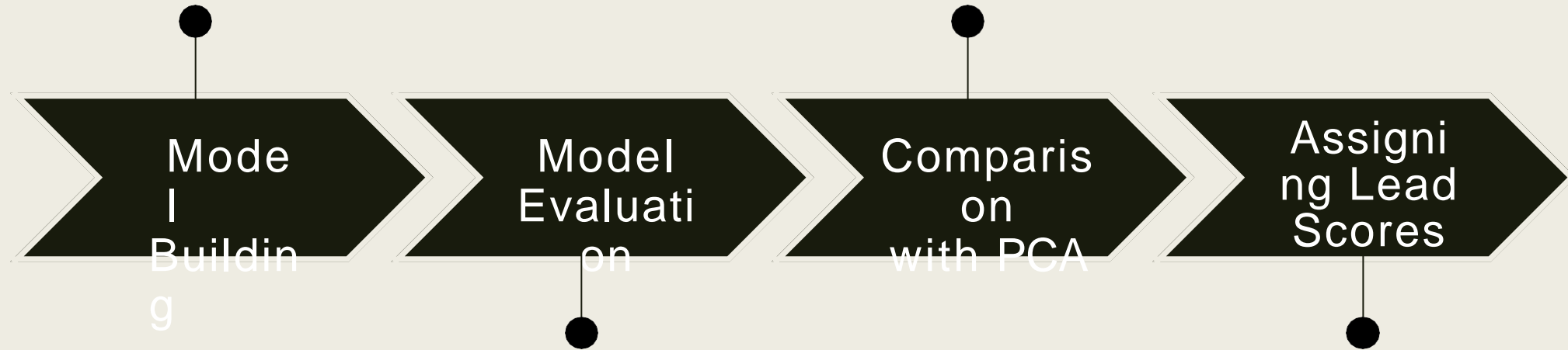- Removing duplicate data and other redundancies
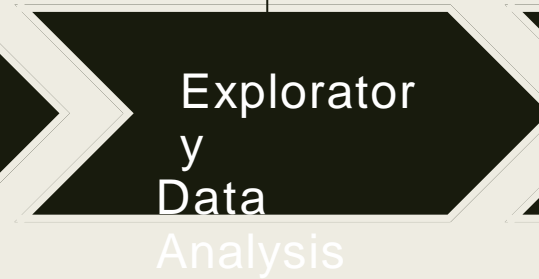
- Outlier treatment
- Dropping unnecessary columns

- Feature standardization
- Feature selection using RFE • Manual feature elimination based on p-values and VIFs

- Dummy variable creation
- Building another model using PCA
- Comparing the two models

Model Building

Model Evaluation

Comparison with PCA

Assigning Lead Scores

- Evaluating model based on various evaluation metrics

Lead Score = Probability * 100

- Finalizing the first model
- Using predicted probabilities to calculate Lead Scores:

- Finding the optimal probability threshold

Numerical Variables
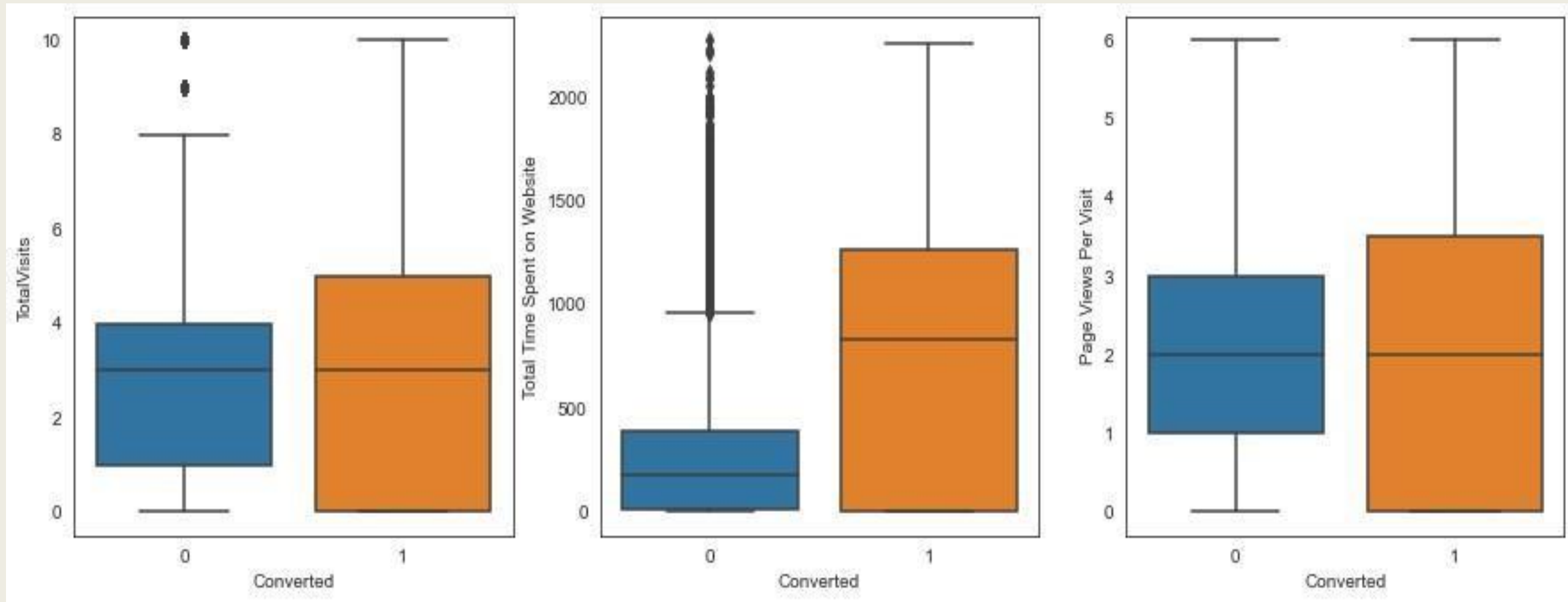

People spending more time on website are more likely to
get converted.

Lead Origin
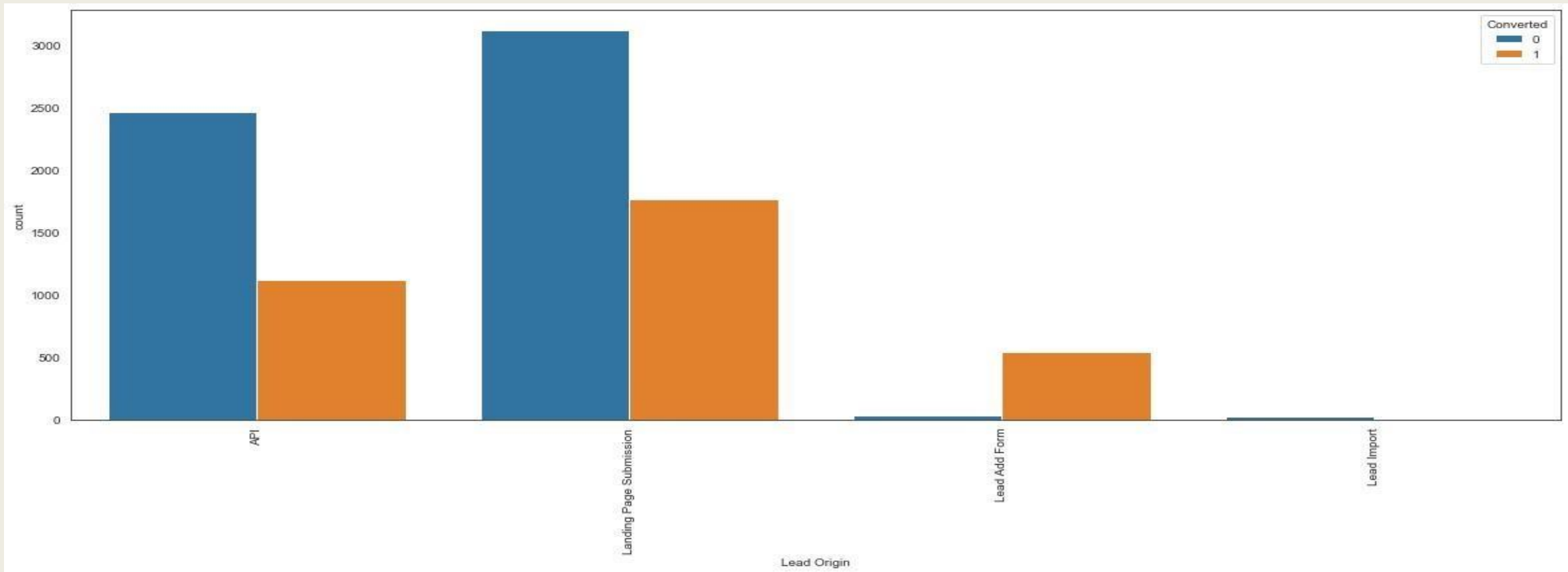
- *'API'* and *'Landing Page Submission'* generate the most leads but have less conversion rates, whereas *'Lead Add Form'* generates less leads but conversion rate is great.
- Try to increase conversion rate for 'API' and 'Landing Page Submission', and
increase leads generation using 'Lead Add Form'

Lead Source
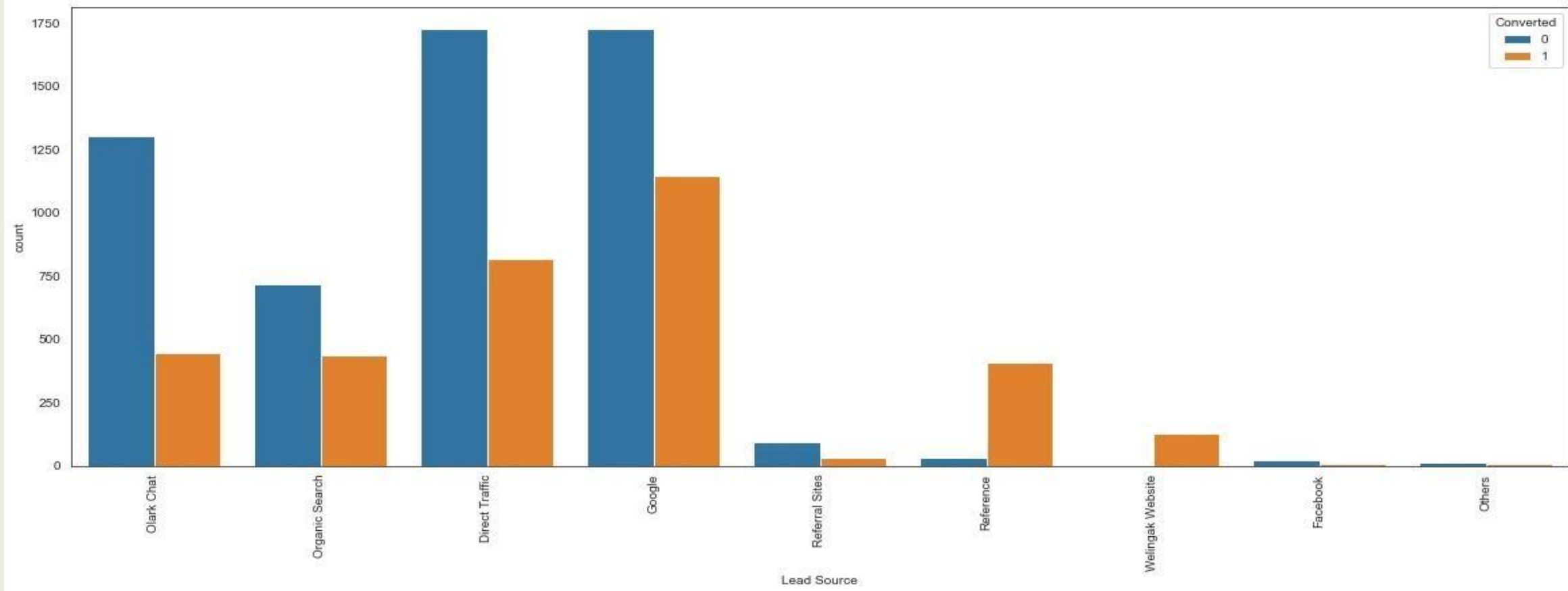
Very high conversion rates for lead sources 'Reference' and 'Welingak Website'. Most leads are generated through 'Direct Traffic' and 'Google'.

Current Occupation
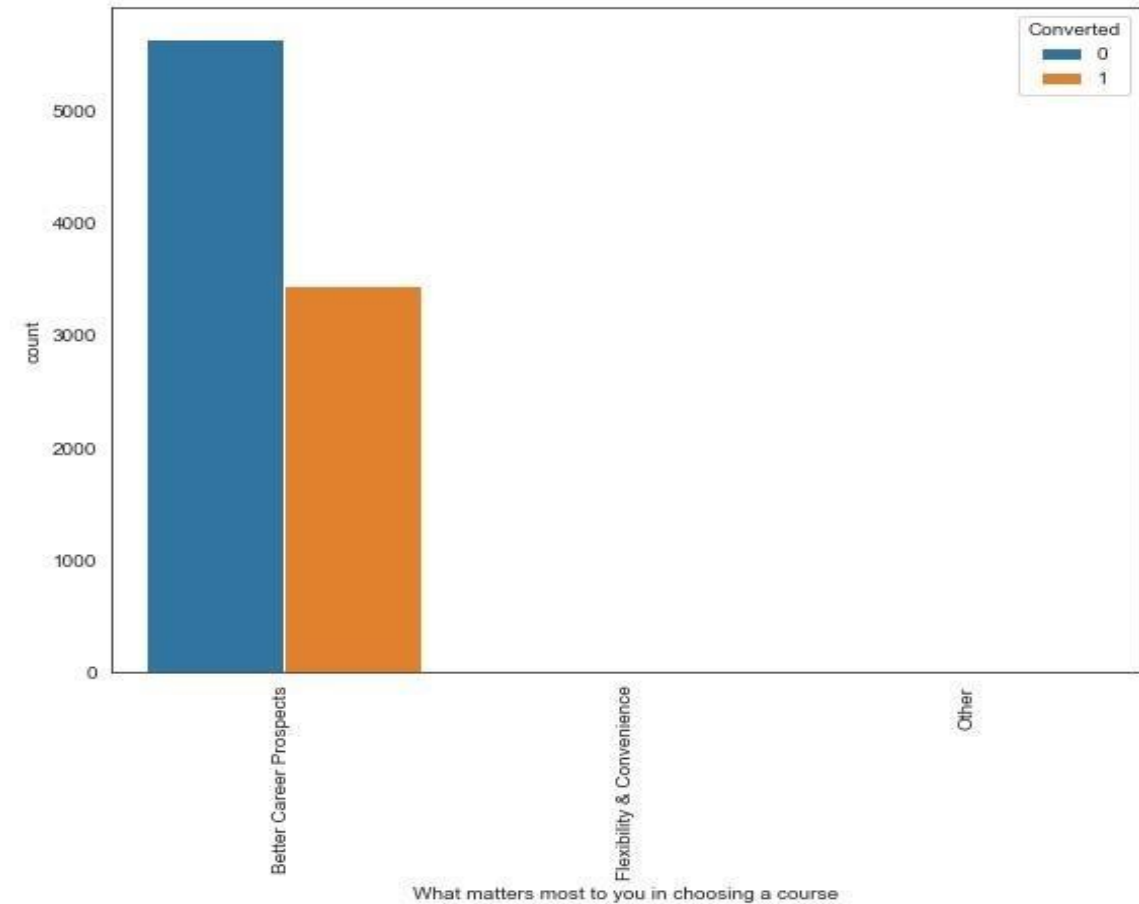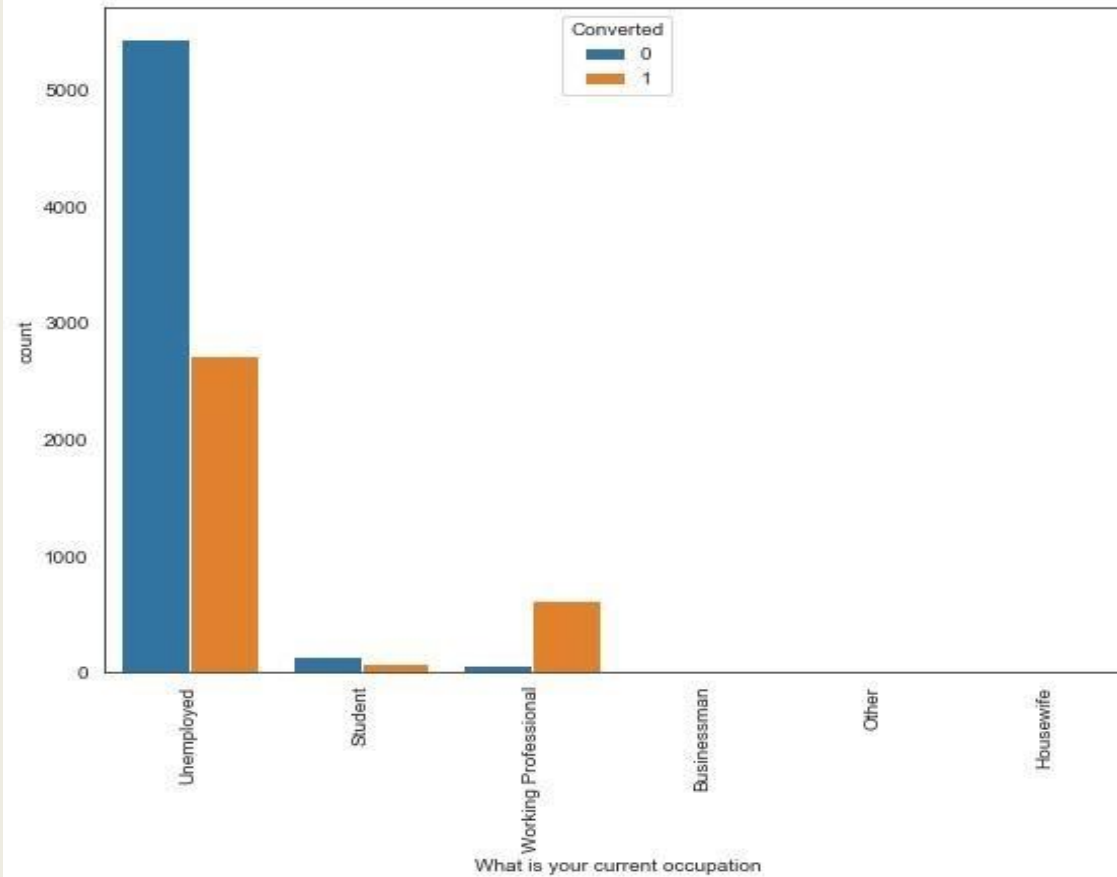
Working Professionals are most likely to get converted.

Tags
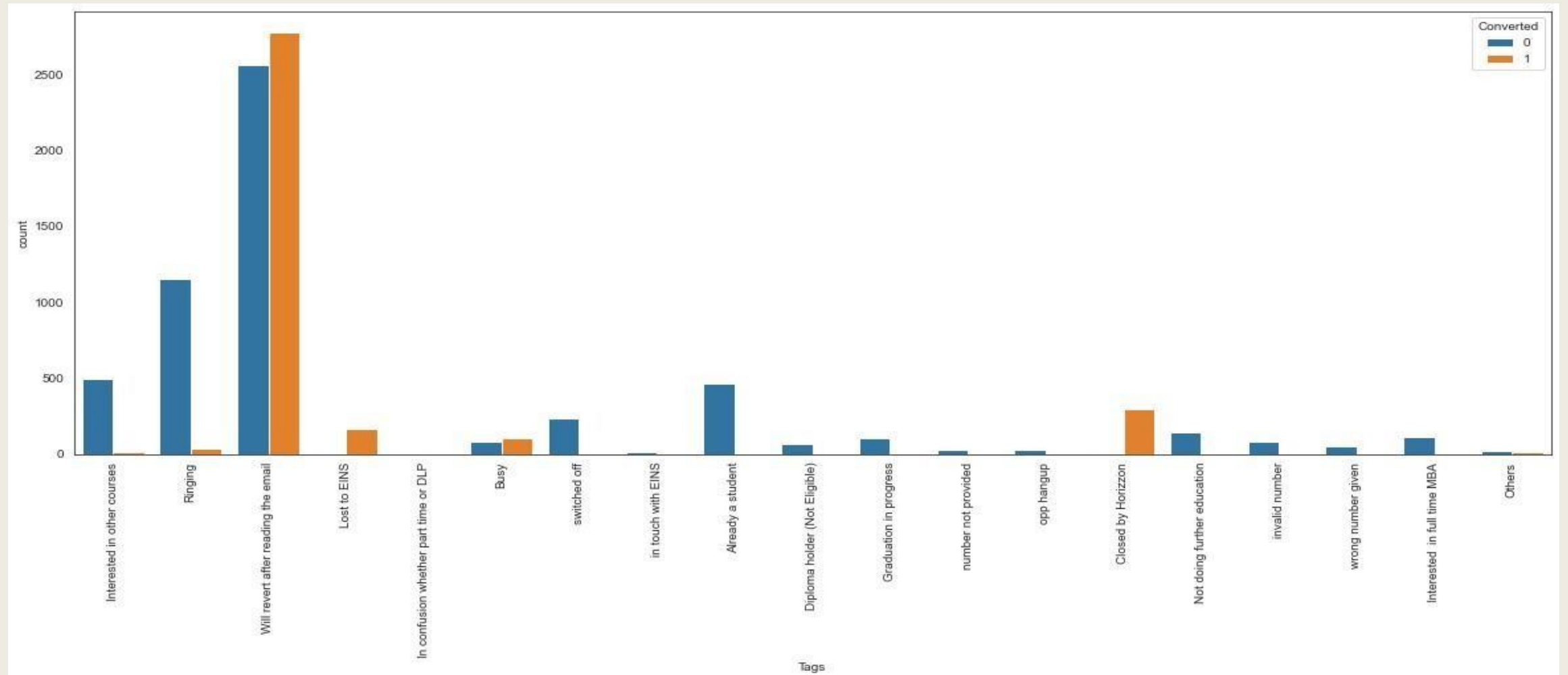
High conversion rates for tags 'Will revert after reading the email', 'Closed by Horizon', 'Lost to EINS', and 'Busy'.

Last Notable Activity

Highest conversion rate is for the last notable activity 'SMS Sent'.
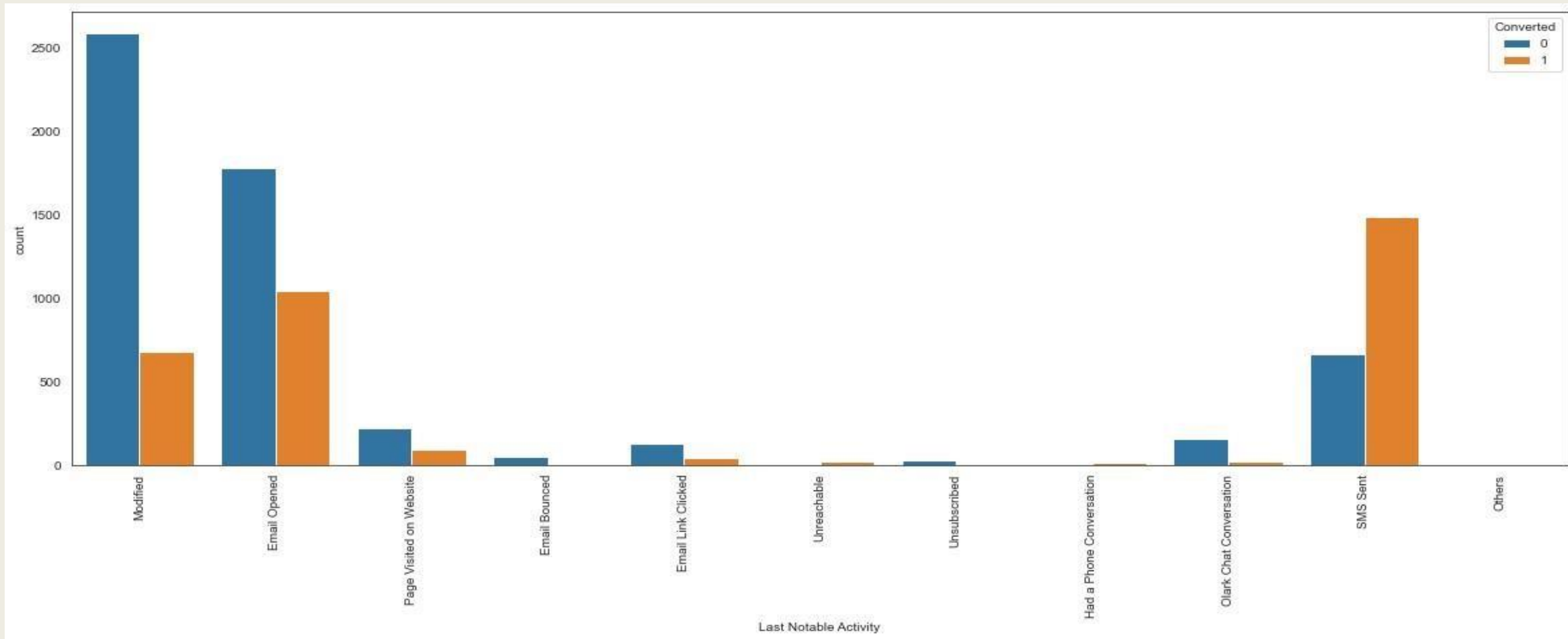
```
                    Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:              Converted    No. Observations:                6351
Model:                            GLM    Df Residuals:                    6338
Model Family:                Binomial    Df Model:                          12
Link Function:                  logit    Scale:                         1.0000
Method:                          IRLS    Log-Likelihood:                -1601.0
Date:                Mon, 18 May 2020    Deviance:                      3202.0
Time:                        02:23:54    Pearson chi2:                 3.48e+04
No. Iterations:                     8
Covariance Type:            nonrobust
==============================================================================
                                      coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const                              -1.9192      0.211     -9.080      0.000      -2.333      -1.505
Do Not Email                       -1.2835      0.212     -6.062      0.000      -1.698      -0.868
Lead Origin_Lead Add Form           1.2035      0.368      3.267      0.001       0.482       1.925
Lead Source_Welingak Website        3.2825      0.820      4.002      0.000       1.675       4.890
Tags_Busy                           3.8043      0.330     11.525      0.000       3.157       4.451
Tags_Closed by Horizzon             7.9789      0.762     10.467      0.000       6.485       9.473
Tags_Lost to EINS                   9.1948      0.753     12.209      0.000       7.719      10.671
Tags_Ringing                       -1.8121      0.336     -5.401      0.000      -2.470      -1.154
Tags_Will revert after reading the email  3.9906  0.228   17.508      0.000       3.544       4.437
Tags_switched off                  -2.4456      0.586     -4.171      0.000      -3.595      -1.297
Lead Quality_Not Sure              -3.5218      0.126    -28.036      0.000      -3.768      -3.276
Lead Quality_Worst                 -3.9106      0.856     -4.567      0.000      -5.589      -2.232
Last Notable Activity_SMS Sent      2.7395      0.120     22.907      0.000       2.505       2.974
==============================================================================
```
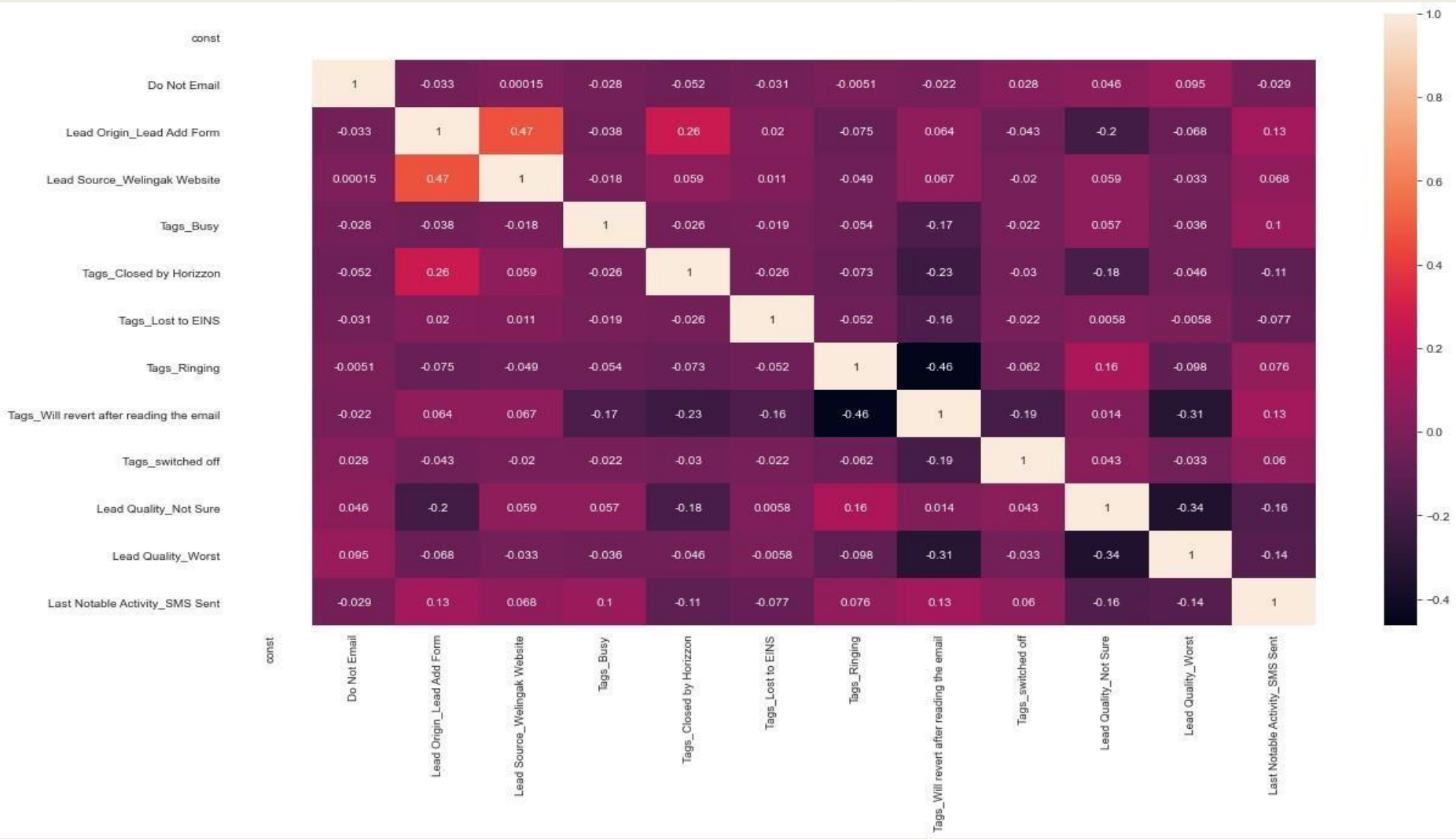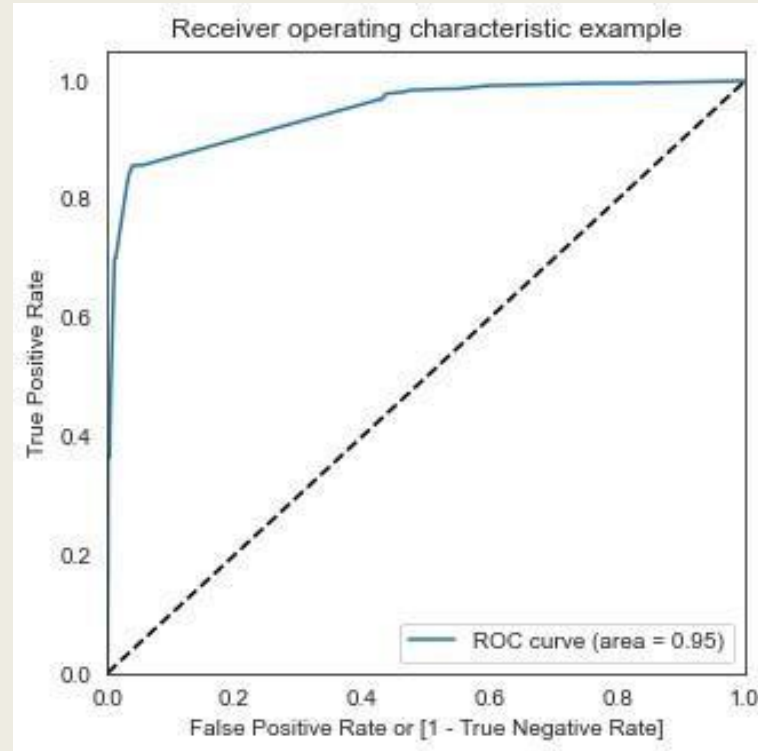
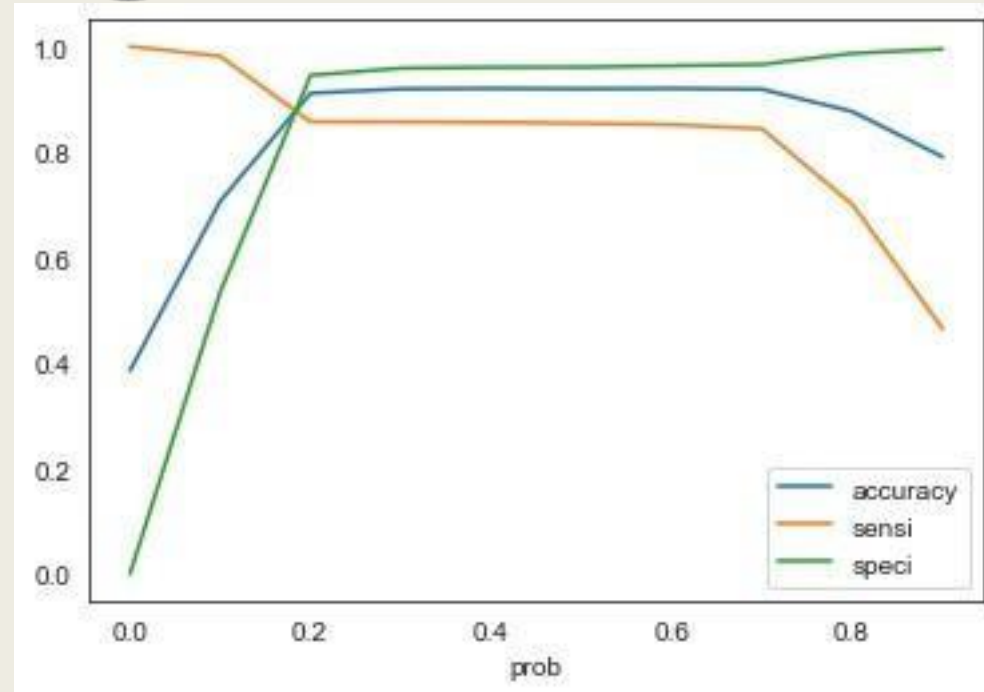**Final Model Summary: All p-values are zero.**

Heatmap

ROC curve

Correlations between features in the final model are negligible.
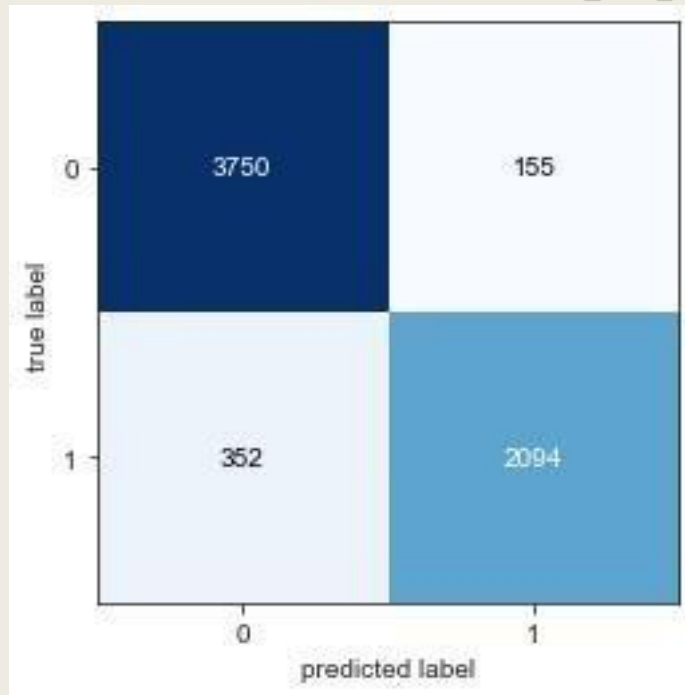

Area under curve =
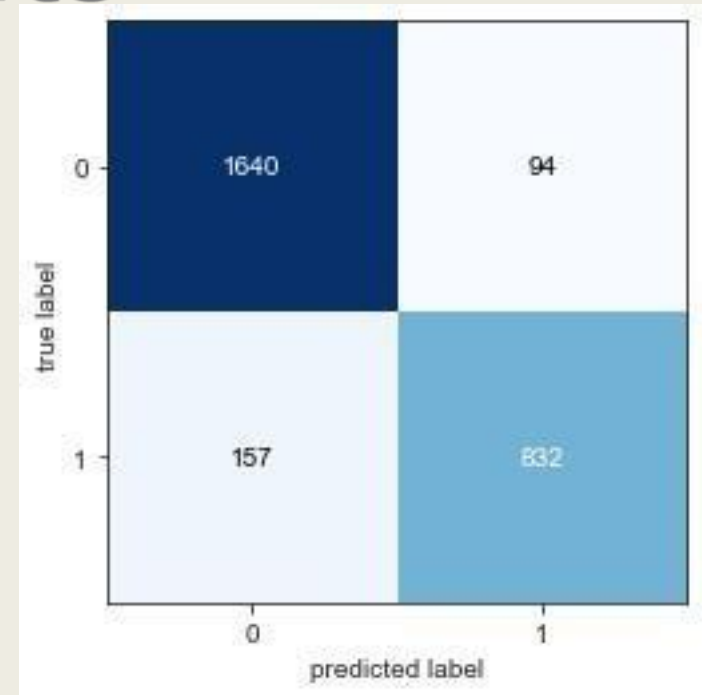0.95

Finding Optimal Threshold

Graph showing changes in Sensitivity, Specificity and Accuracy with changes in the probability threshold values

Optimal cutoff = 0.20

Confusion Matrix
Final Results

For train
set

For test
set

Data	Train set	Test set
Accuracy	0.9111	0.9078
Sensitivity	0.8573	0.8412
Specificity	0.9449	0.9457
False Positive Rate	0.0550	0.0542
Positive Predictive Value	0.9070	0.8984
Negative Predictive Value	0.9135	0.9126
AUC	0.9488	0.9388

Relative Importance Of Features
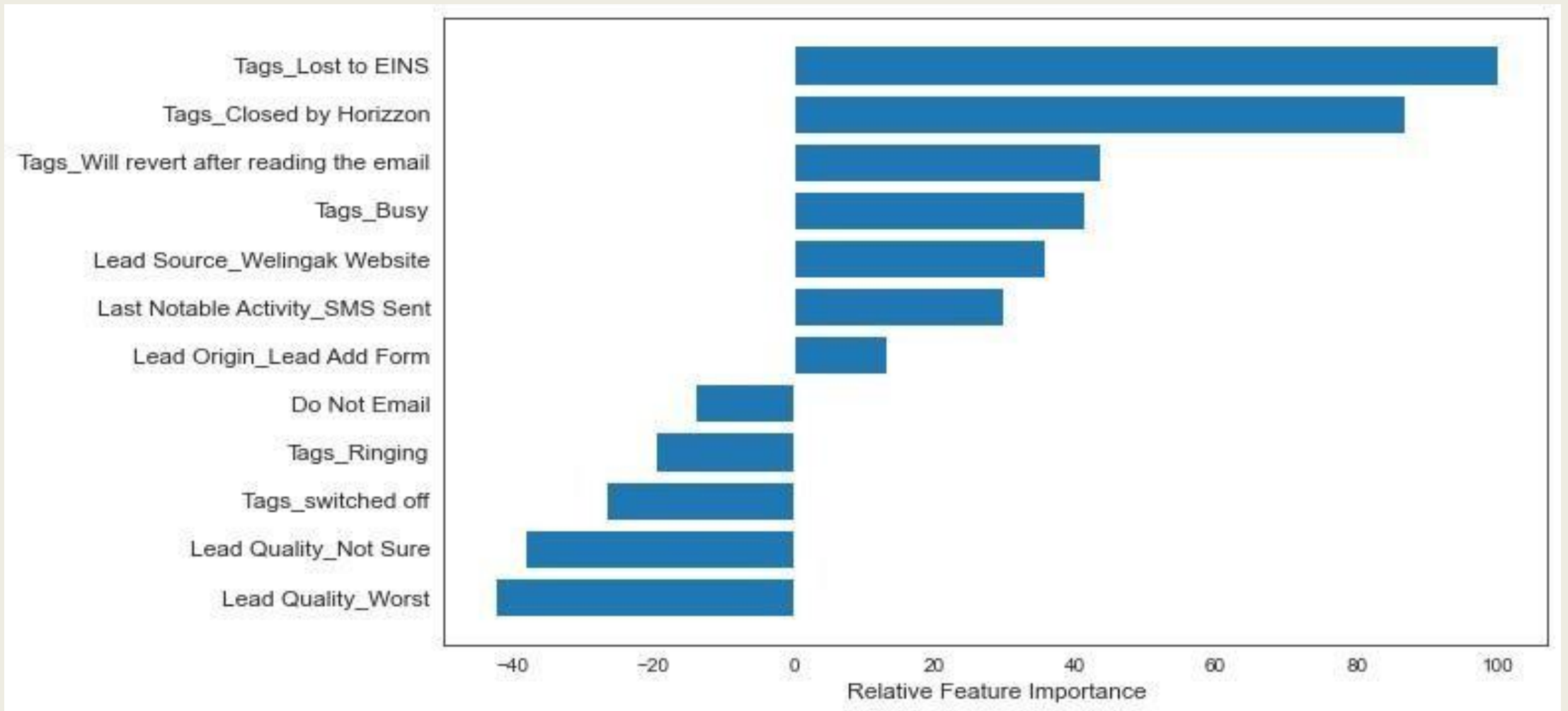
Feature Importance

- Three variables which contribute most towards the probability of a lead conversion in decreasing order of impact are:

  I. *Tags_Lost to EINS*

  II. Tags_Closed by Horizzon

  III. Tags_Will revert after reading the email

- These are dummy features created from the categorical variable Tags.

- All three contribute positively towards the probability of a lead conversion.

- These results indicate that the company should focus more on the leads with these three tags.

Situation 1: Company has interns for 2 months. They wish to make lead conversion more aggressive. They want almost all of the potential leads to be converted and hence, want to make phone calls to as much of such people as possible. Solution:

- $Sensitivity = TruePositives / (TruePositives + FalseNegatives)$

- Sensitivity can be defined as the number of actual conversions predicted correctly out of total number of actual conversions. As we saw earlier, sensitivity decreases as the threshold increases.

- High sensitivity implies that our model will correctly predict almost all leads who are likely to convert. At the same time, it may overestimate and misclassify some of the non-conversions as conversions.

- As the company has extra man-power for two months and wants to make the lead conversion more aggressive, it is a good strategy

Situation 2: At times, the company reaches its target for a quarter before the deadline. It wants the sales team to focus on some new work. So during this time, the company's aim is to not make phone calls unless it's extremely necessary.

Solution:

- $Specificity = TrueNegatives/(TrueNegatives + FalsePositives)$

- Specificity can be defined as the number of actual non-conversions predicted correctly out of total number of actual non-conversions. It increases as the threshold increases.

- High specificity implies that our model will correctly predict almost all leads who are not likely to convert. At the same time, it may misclassify some of the conversions as non-conversions.

- As the company has already reached its target for a quarter and doesn't want to make unnecessary phone calls, it is a good strategy

○ It will ensure that the phone calls are only made to customers who have a very high probability of conversion. To achieve high specificity, we need to choose a high threshold value.

Recommendations

■ By referring to the data visualizations, focus on

– *Increasing the conversion rates for the categories generating more leads and*

– *Generating more leads for categories having high conversion rates.*

- Pay attention to the relative importance of the features in
  the model and their positive or negative impact on the probability of conversion.

- Based on varying business needs, modify the probability threshold value for identifying potential leads.